Theory and model of thalamocortical processing in decision making under uncertainty

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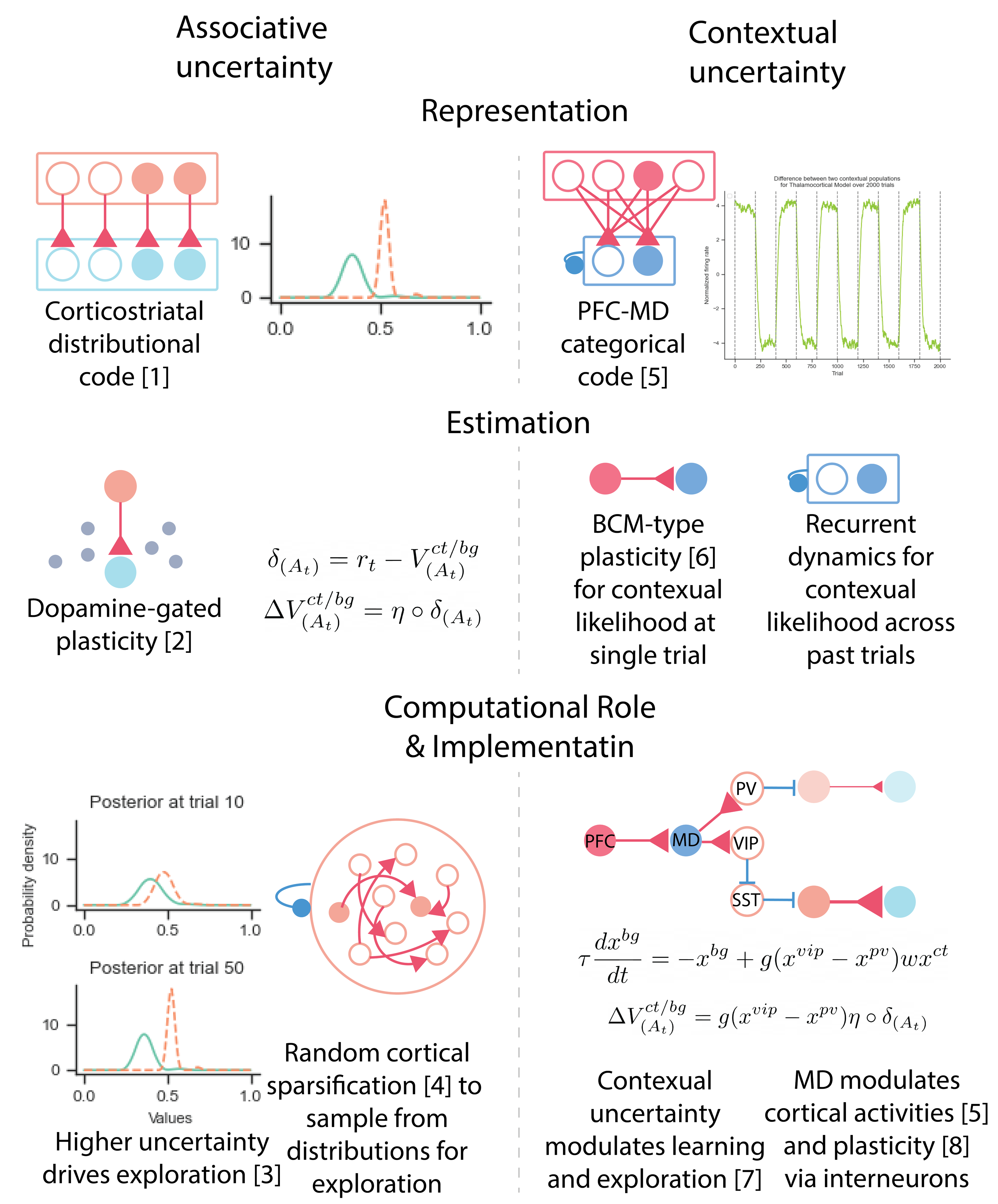
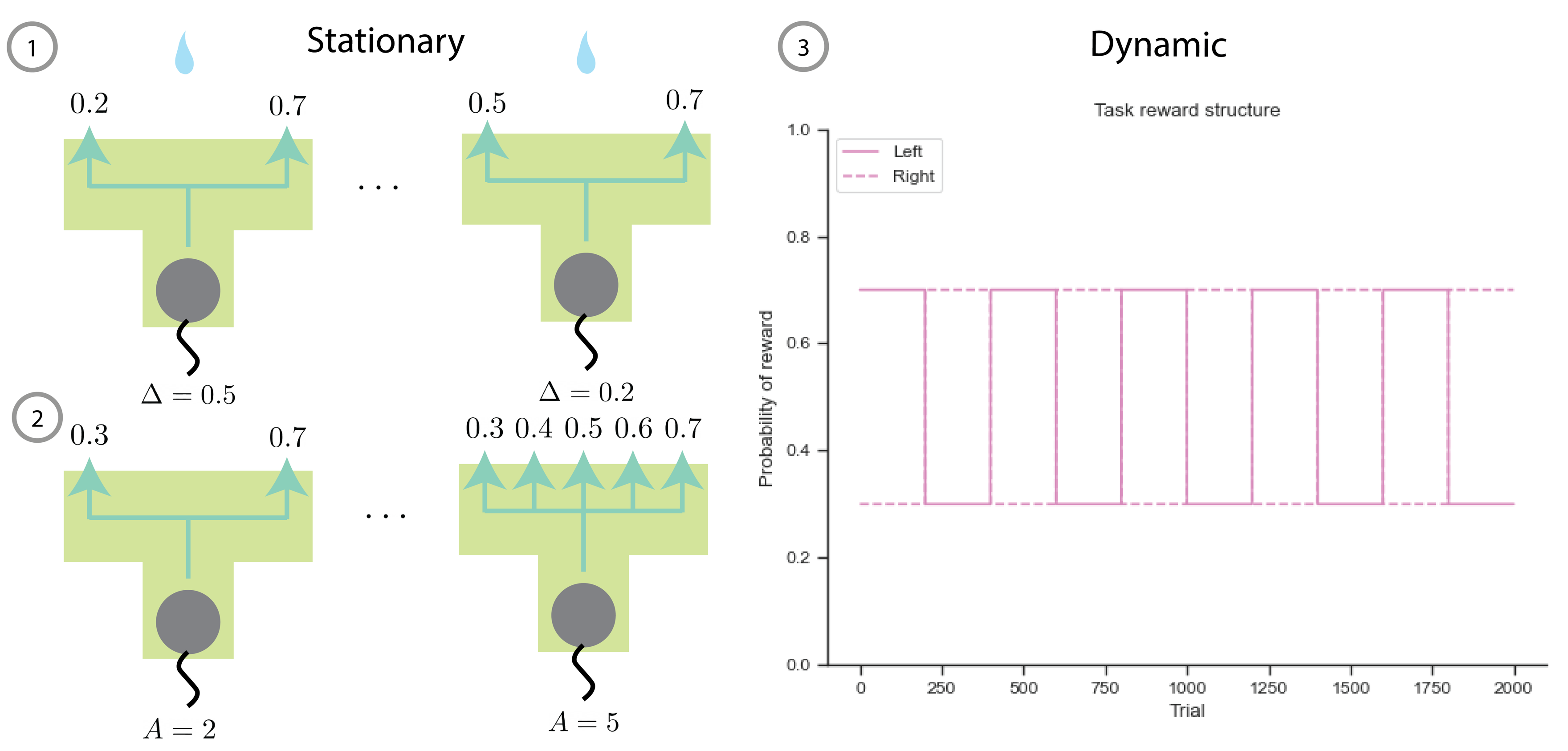
Motivation

- Animals flexibly select actions that maximize future rewards despite facing uncertainty in sensory inputs, action-outcome associations or contexts.
- The computational and circuit mechanisms underlying the representation, estimation and computational role of uncertainty are poorly understood.
- Animal experiments indicate that the thalamocortical-basal ganglia loop represents different forms of uncertainty.
- Normative models excel at providing insights on computational roles of uncertainty, but they cannot be directly related to neural mechanisms.
- A gap exists between what we know about the neural representation of uncertainty and the computational functions uncertainty serves in cognition.

A mechanistic neural model



Task



KEY REFERENCES

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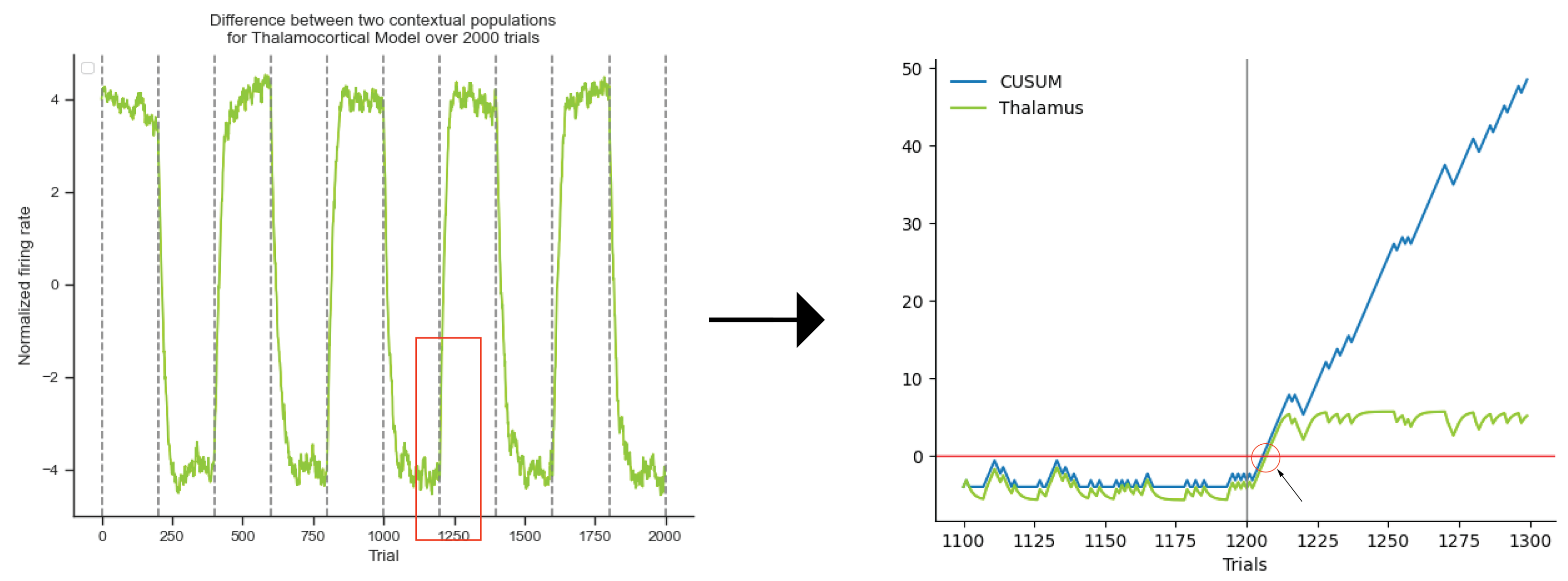
Approximation to normative models

- It is usually difficult to understand a mechanistic model on a computational level due to its complexity.
- To overcome this, we mathematically approximate our mechanistic model to a novel normative model and analyze its functions and performance.

Theorem 1. *If we choose the sparsity K, initial corticostriatal weight $\{\hat{V}^{ct/bg}_{(a)}\}_{a\in[A]}$, the learning rate $\{\eta_{(t)}\}_{t\in[T]}$ appropriately, then the regret of the normative model after T trials in a static A-AFC task is at most $C\sqrt{AT\log(AT)}$ for some constant C.*

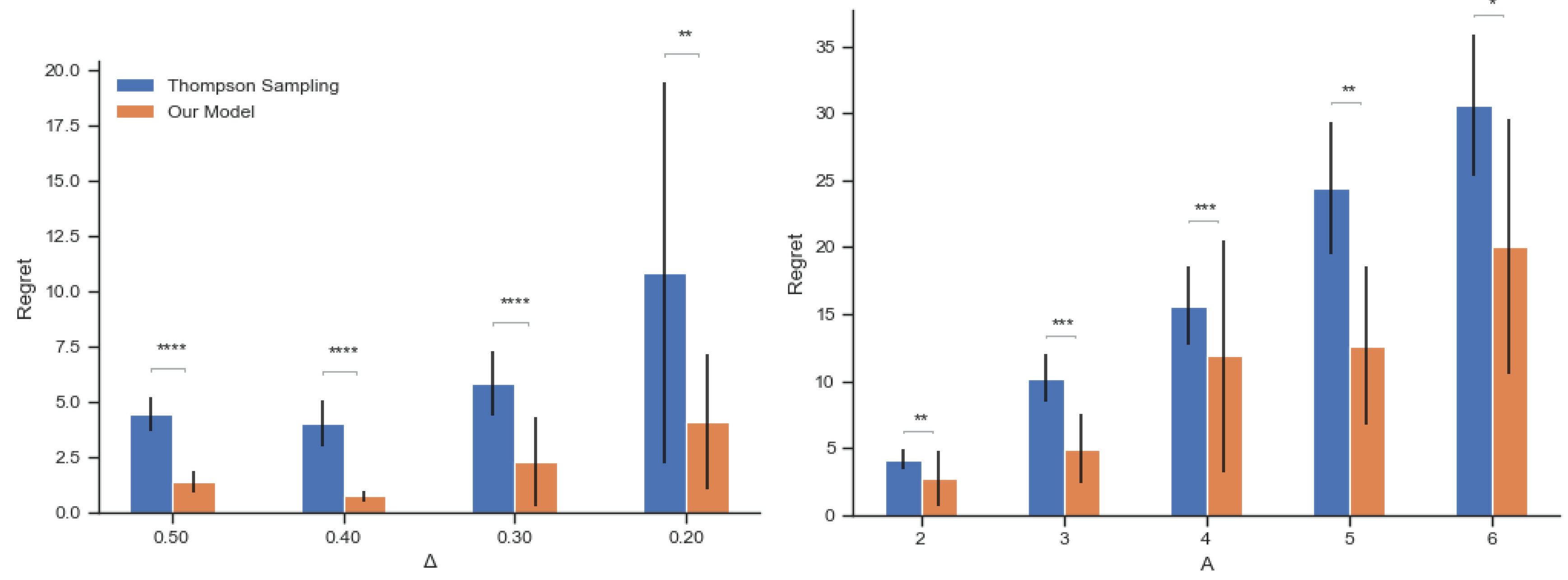
It has been shown that no algorithm can achieve regret smaller than $\Theta(\sqrt{AT})$ [9], so our normative model has near-optimal performance.

Theorem 2. *After PFC-MD synapses learn the contextual generative model $P(a_t, r_t|c)$, our PFC-MD circuit approximates to a multiple change points generalization of CUSUM algorithm, an algorithm that is known to detect single environmental changes optimally [10].*

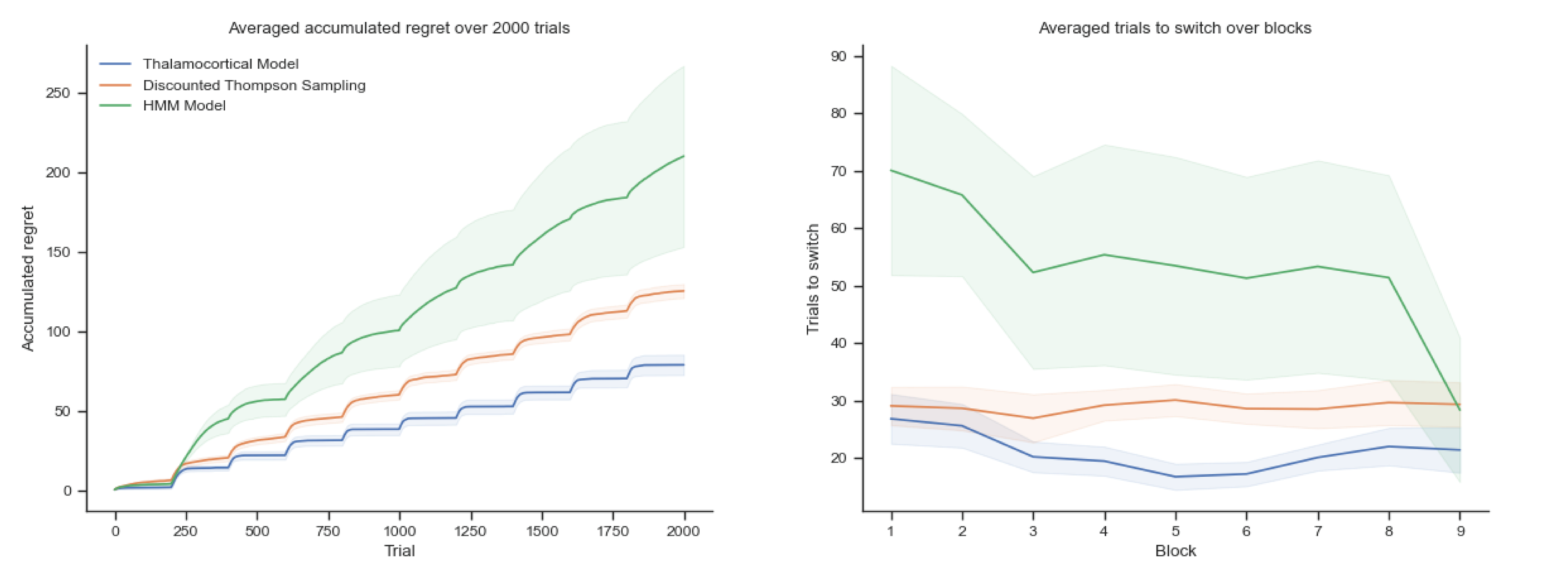


Our PFC-MD circuit approximates a normative model that can detect sequential environmental changes optimally.

Experimental results



Our mechanistic model performs efficient exploration in a variety of static environments compared to Thompson sampling.



Our model learns how to more flexibly switch its behaviors in dynamic environments compared to other widely used algorithms.

Summary and future works

- Our work links computational insights, normative models and neural realization together in decision-making under various forms of uncertainty.
- In the future, we would like to combine the population dynamic approach to create a comprehensible mechanistic model in a more data-driven manner.